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Research article

Verifiable soil organic carbon modelling to facilitate regional reporting of cropland carbon change: A test case in the Czech Republic

Juraj Balkovič [a,b,*], Mikuláš Madaras [c], Rastislav Skalský [a,d], Christian Folberth [a], Michaela Smatanová [e], Erwin Schmid [f], Marijn van der Velde [g], Florian Kraxner [a], Michael Obersteiner [a,h]

[a] International Institute for Applied Systems Analysis, Ecosystems Services and Management Program, Schlossplatz 1, A-2361, Laxenburg, Austria
[b] Faculty of Natural Sciences, Comenius University in Bratislava, Ilkovičova 6, 842 15, Bratislava, Slovak Republic
[c] Crop Research Institute, Division of Crop Management Systems, Drnovská 507/73, 161 06, Praha 6 – Ruzyně, Czech Republic
[d] National Agricultural and Food Centre, Soil Science and Conservation Research Institute, Trenčianska 55, 821 09, Bratislava, Slovak Republic
[e] Central Institute for Supervising and Testing in Agriculture, Hroznová 63/2, 656 06, Brno, Czech Republic
[f] Institute for Sustainable Economic Development, University of Natural Resources and Life Sciences, Vienna, Feistmantelstrasse 4, 1180, Vienna, Austria
[g] European Commission, Joint Research Centre, 21027, Ispra, Italy
[h] Environmental Change Institute, University of Oxford, South Parks Road, Oxford, OX1 3QY, United Kingdom

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ABSTRACT

Regional monitoring, reporting and verification of soil organic carbon change occurring in managed cropland are indispensable to support carbon-related policies. Rapidly evolving gridded agronomic models can facilitate these efforts throughout Europe. However, their performance in modelling soil carbon dynamics at regional scale is yet unexplored. Importantly, as such models are often driven by large-scale inputs, they need to be benchmarked against field experiments. We elucidate the level of detail that needs to be incorporated in gridded models to robustly estimate regional soil carbon dynamics in managed cropland, testing the approach for regions in the Czech Republic. We first calibrated the biogeochemical Environmental Policy Integrated Climate (EPIC) model against long-term experiments. Subsequently, we examined the EPIC model within a top-down gridded modelling framework constructed for European agricultural soils from Europe-wide datasets and regional land-use statistics. We explored the top-down, as opposed to a bottom-up, modelling approach for reporting agronomically relevant and verifiable soil carbon dynamics. In comparison with a no-input baseline, the regional EPIC model suggested soil carbon changes (~0.1–0.5 Mg C ha^{-1} y^{-1}) consistent with empirical-based studies for all studied agricultural practices. However, inaccurate soil information, crop management inputs, or inappropriate model calibration may undermine regional modelling of cropland management effect on carbon since each of the three components carry uncertainty (~0.5–1.5 Mg C ha^{-1} y^{-1}) that is substantially larger than the actual effect of agricultural practices relative to the no-input baseline. Besides, inaccurate soil data obtained from the background datasets biased the simulated carbon trends compared to observations, thus hampering the model's verifiability at the locations of field experiments. Encouragingly, the top-down agricultural management derived from regional land-use statistics proved suitable for the estimation of soil carbon dynamics consistently with actual field practices. Despite sensitivity to biophysical parameters, we found a robust scalability of the soil organic carbon routine for various climatic regions and soil types represented in the Czech experiments. The model performed better than the tier 1 methodology of the Intergovernmental Panel on Climate Change, which indicates a great potential for improved carbon change modelling over larger political regions.

* Corresponding author. International Institute for Applied Systems Analysis, Ecosystems Services and Management Program, Schlossplatz 1, A-2361, Laxenburg, Austria.

E-mail addresses: balkovic@iiasa.ac.at, juraj.balkovic@uniba.sk (J. Balkovič), madaras@vurv.cz (M. Madaras), skalsky@iiasa.ac.at, r.skalsky@vupop.sk (R. Skalský), folberth@iiasa.ac.at (C. Folberth), michaela.smatanova@ukzuz.cz (M. Smatanová), erwin.schmid@boku.ac.at (E. Schmid), Marijn.VAN-DER-VELDE@ec.europa.eu (M. van der Velde), kraxner@iiasa.ac.at (F. Kraxner), oberstei@iiasa.ac.at (M. Obersteiner).

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1. Introduction

Agricultural management practices that increase soil organic carbon (SOC) stocks are prominent nature-based solutions contributing to climate mitigation (IPCC, 2000; Smith et al., 2019) and a more resilient and sustainable agriculture (Lal, 2004). Continuous monitoring, reporting and verification of SOC stocks in agricultural soils has therefore been proposed as a key element in ensuring the contribution of soil management to climate change mitigation (Rumpel et al., 2018). Yet, monitoring, reporting and verification of SOC dynamics occurring due to agricultural soil management is challenging when inventorying large areas (Smith et al., 2020). To facilitate SOC change assessment across regions, and to improve CO_2 emission inventories, gridded agronomic models (GAM) provide a promising way forward. Process-based GAMs such as those based on the Environmental Policy Integrated Climate model (EPIC, Izaurralde et al., 2006; Williams, 1995) are particularly suitable to predict the effects of agricultural management on soil carbon in conjunction with crop yields as they simulate relevant biogeochemical processes as well as various crop management options across a variety of landscapes. However, as GAMs are driven by large-scale input data, they need to be benchmarked against long-term field experiments and measurement networks (Rumpel et al., 2018; Smith et al., 2020, 2012), and implement agricultural management and soils representative of actual practices and soils in the field. These aspects, which determine to a large extent the capacity of GAMs to support regional carbon assessments and accounting, however, have not yet been satisfactorily explored. In this paper, we describe an elaborate modelling effort and sensitivity analysis of key model parameters to elucidate the level of detail that needs to be incorporated in GAMs – exemplary for the well-established gridded model EPIC-IIASA (Balkovič et al., 2014) – to robustly estimate regional SOC changes. We confront and analyse results from 1) EPIC model simulations of long-term experiments (LTE) at the field scale, 2) gridded EPIC-IIASA (Balkovič et al., 2014, 2013) regional simulations with known agricultural practices (bottom-up), and 3) gridded EPIC-IIASA simulations with practices derived from regional crop statistics (top-down).

Although the EPIC model has been developed for field scale simulations, the EPIC-based GAMs such as EPIC-IIASA have been extensively applied globally of for selected regions such as Europe. They have been evaluated as robust solutions for agriculture sector assessments (Müller et al., 2016; Rosenzweig et al., 2014). A general concern regarding gridded agronomic modelling is that often coarse input data and a lack of calibration for local environmental conditions may limit the models' performance at farm and field scales (van Ittersum et al., 2013) – the scale at which agricultural practices are experimentally tested and monitored. Meteorological variables, soil properties and crop management input data scaled to meet the target grid resolution are typical sources of bias. Whilst scaling of meteorological data has already been thoroughly explored (Angulo et al., 2013; Zhao et al., 2015), handling of crop management and soil inputs in GAMs has received little attention (Folberth et al., 2019, 2016).

There are several concerns about soil and crop management input data that need to be addressed to foster GAM applications for regional carbon accounting. Firstly, localization of a single soil profile to simulation grid, a common practice in GAMs (Balkovič et al., 2013; Elliott et al., 2015; Rosenzweig et al., 2014), allows only a partial accounting of true soil diversity (Costantini and L'Abate, 2016), which may challenge crop modelling results in regions with heterogeneous soils (Folberth et al., 2016). The likelihood of misallocated soil properties is also quite high given that soil maps underlying the models are greatly generalized (Costantini and L'Abate, 2016; Hoffmann et al., 2016). Secondly, crop management data are often coarse and incomplete at regional scale. Crop calendars, crop distribution, organic and mineral fertilization intensities, irrigation and soil cultivation practices are commonly inferred only for administrative regions or large grid cells with lacking temporal resolution (Elliott et al., 2015; Mueller et al., 2012; Sacks et al., 2010; Wriedt et al., 2009). Such crop management data may significantly deviate from on-ground agricultural practices (van Ittersum et al., 2013). Finally, a lack of knowledge about model parameters in different environments is a substantial pool of uncertainty (Folberth et al., 2019). Although calibration against benchmark experimental sites could reduce this to a reasonable level, this uncertainty cannot be completely neglected since field experiments are scarce in many regions (Jandl et al., 2014; Lorenz et al., 2019). A detailed uncertainty analysis is therefore required to help prioritise activities related to model development and to benchmark reliability (Smith et al., 2020, 2012).

The main objective of this study is to explore the applicability of EPIC-IIASA gridded model for reporting agronomically relevant SOC changes, exemplary in study regions of the Czech Republic. To communicate model performance, we investigated 1) the importance and influence of model calibration at benchmark sites, 2) localization of soil properties to grid cells, 3) regionalization of agricultural practices based on crop statistics, and 4) the model's verifiability at field scale by long-term SOC observations. We addressed the most common soil-based agricultural practices such as mineral fertilization, farmyard manure amendments, crop residue incorporation, and crop rotations. Special attention was paid to the top-down crop management setup, an inherent component in EPIC-IIASA model, as opposed to a bottom-up approach where known in-situ agricultural practices are extended to all cropland in regions. To better communicate reliability and constrains in our platform, we trace the uncertainty added by each of the components listed above, and we explored which of the platform's parameters, variables and inputs (hereafter collectively referred to as the features) dominated the simulated SOC change variability at local to regional scales. The case study we present here provides a template for reporting-oriented SOC modelling, accounting for the uncertainty that comes into play when considering the regional variability in soils and the need to derive representative soil and crop management inputs at regional scale.

2. Methods

2.1. Long-term field experiments and study area

Experimental plots form a total of four long-term field experimental stations established between 1955 and 1979 were used in this study (Table 1). All experiments were designed to optimize fertilization schemes under diverse soil and climatic conditions in the Czech Republic, ranging from lowland (Uherský Ostroh; 186 m altitude) to submountain regions (Trutnov, 417 m), and from Luvisols (Hněvčeves) to Cambisols (Trutnov and Uherský Ostroh). A more detailed description of LTEs can be found in Kunzová (2013), Lipavský et al. (2008), Madaras et al. (2014), Madaras and Lipavský (2009), Šimon and Czakó (2014), and in Text A.1. In this study we used in-situ soil and meteorological inputs, detailed crop management data from experiment logs as well as the observed time series of crop yield (in t dry matter ha^{-1}) and topsoil organic carbon concentration (in %). Since changes in bulk density have not been consistently monitored in the past, the recent bulk density measurements reported in the above-mentioned field studies were used to calculate carbon stocks.

Experimental plots with the following crop treatments were employed in this study:

1) Control plots (Cntr) with no fertilizer inputs from the beginning of the experiments, all crop residues harvested.
2) Mineral N and P fertilization only (NP, crop-specific fertilizer application rates are summarized in Table 1), all crop residues harvested.
3) Mineral N and P fertilization combined with farmyard manure applications (NP + FYM, see Table 1 for application rates), all crop residues harvested.
4) Farmyard manure applications only (FYM), all crop residues harvested.

Table 1
Long-term experiments in the Czech Republic (af: alfalfa, bl: barley, cl: clover, cs: corn silage, mz: corn maize, ot: oats, po: potato, rp: rape, sg: sugar beet, sw: spring wheat, wr: winter rye, ww: winter wheat; bl/af: mix of barley and alfalfa; bl(ot): barley or oats; N: nitrogen, P: phosphorus, FYM: farmyard manure).

LTE	Crop rotation (LTERot)	Experimental treatment	Nutrient input
Hněvčeves N: 50.31° E: 15.71° Duration: 1980–2016	bl-sg-bl-bl/af-af-ww-cs-ww	Cntr	No fertilization
		NP	bl (30–90 kg N ha^{-1}, 25–60 kg P ha^{-1}), sg (100–150 kg N ha^{-1}, 30–50 kg P ha^{-1}), af (40 kg N ha^{-1}, 60 kg P ha^{-1}), ww (70–140 kg N ha^{-1}, 25–50 kg P ha^{-1}), cs (120–170 kg N ha^{-1}, 50 kg P ha^{-1})
		NP + FYM	Mineral fertilizers as in NP, 30–40 Mg FYM ha^{-1} for maize and sugar beet
Trutnov N: 50.56° E: 15.89° Duration: 1966–2009	po-bl(ot)-cl (wr)-cl(wr)-ww	Cntr	No fertilization
		NP	po (75–95 kg N ha^{-1}, 20–45 kg P ha^{-1}), bl (40–80 kg N ha^{-1}, 20–63 kg P ha^{-1}), ot (60–80 kg N ha^{-1}, 10–25 kg P ha^{-1}), cl (30 kg N ha^{-1}, 25–30 kg P ha^{-1}), wr (90 kg N ha^{-1}, 25–45 kg P ha^{-1}), ww (60–90 kg N ha^{-1}, 25–30 kg P ha^{-1})
		NP + FYM	Mineral fertilizers as in NP, 20–40 Mg FYM ha^{-1} for potatoes and occasionally 14–20 Mg FYM ha^{-1} for winter rye
		FYM	20–40 Mg FYM ha^{-1} for potatoes and occasionally 14–20 Mg FYM ha^{-1} for winter rye
		NP + resid	Mineral fertilizers as in NP, 4.5–8 Mg ha^{-1} of straw for potatoes, occasionally 4.5 Mg ha^{-1} of straw for winter rye
Ruzyně N: 50.09° E: 14.30° Duration: 1954–2017	sg-af(bl)-af (rp)-af(rp)-ww since 1966: sg-sw	Cntr	No fertilization
		NP	af (50 kg N ha^{-1}, 53 kg P ha^{-1}), bl (50 kg N ha^{-1}, 53 kg P ha^{-1}), rp (150 kg N ha^{-1}, 53 kg P ha^{-1}), ww (50–100 kg N ha^{-1}, 53 kg P ha^{-1}), sw (50 kg N ha^{-1}, 53 kg P ha^{-1}), sg (150 kg N ha^{-1}, 53 kg P ha^{-1})
		NP + FYM	Mineral fertilizers as in NP, 21 Mg FYM ha^{-1} for sugar beet
		FYM	21 Mg FYM ha^{-1} for sugar beet
Uherský Ostroh N: 48.99° E: 17.42° Duration: 1972–2017	sg-bl-ot/af-af-ww-po (cs)-ww-bl	Cntr	No fertilization
		NP + FYM	sg (120–240 kg N ha^{-1}, 100 kg P ha^{-1}), bl (50–90 kg N ha^{-1}, 50 kg P ha^{-1}), ot (80 kg N ha^{-1}, 100 kg P ha^{-1}), af (80–100 kg N ha^{-1}, 30 kg P ha^{-1}), ww (100–160 kg N ha^{-1}, 50–100 kg P ha^{-1}), po (160 kg N ha^{-1}, 100 kg P ha^{-1}), cs (190 kg N ha^{-1}, 50 kg P ha^{-1}) 35–43 Mg FYM ha^{-1} for sugar beet, potatoes and maize
		FYM	35–43 Mg FYM ha^{-1} for sugar beet, potatoes and maize

5) Mineral N and P fertilization, crop residues retained (NP + resid).

Given the geographical location of LTEs, three administrative regions were analysed (Fig. 1): Hradec Králové Region (CZ052), Zlín Region (CZ072), and the Capital Prague Region (CZ010). See Text A.1 for more detailed description of the study regions.

2.2. The EPIC-IIASA gridded modelling framework

The EPIC-IIASA GAM (the EU version) was built by coupling EPIC, v. 0810 model (Izaurralde et al., 2006; Williams, 1995, see Text A.2) with EU-wide datasets on land cover, soils, topography and crop management practices (Balkovič et al., 2013). It is constructed for a 1 × 1 km grid covering the EU countries, where each grid cell is attributed with dominant soil properties (see Section 2.2.1), land cover class (CLC2000, https://land.copernicus.eu/pan-european/corine-land-cover), territorial unit (NUTS2 regions, https://ec.europa.eu/eurostat/web/gisco), and daily meteorological data from 1990 to 2017 (Crop Growth Monitoring System, CGMS, see e.g. Van der Velde et al., 2018).

2.2.1. Soil grids

Dominant topsoil (0–30 cm) and subsoil (30–120 cm) properties were calculated for each 1 × 1 km grid cell (hereafter referred to as soil grids) from the underlying soil datasets: the European Soil Bureau Database (ESDB, version 2.0, https://esdac.jrc.ec.europa.eu), the Database of Hydraulic Properties of European Soils (Wösten et al., 1999), and the Map of organic carbon content in the topsoil (Lugato et al., 2014). A total of 13 soil properties as in Balkovič et al. (2013) were used. The mode slope and elevation were derived from the Shuttle Radar Topographic Mission Data (SRTM,Werner, 2001), assuming a 50 ha field size representative of the whole grid cell (Fritz et al., 2015). The Hargreaves method was used to calculate potential evapotranspiration in this study as recommended by Balkovič et al. (2013).

2.2.2. Crop database

The EU version of EPIC-IIASA includes major European crops including winter wheat and rye, spring barley, grain and forage maize, winter rapeseed, sunflower, sugar beet, potatoes, soybean, rice, alfalfa and oats (Balkovič et al., 2018, 2013). Potential heat units and sowing dates of each crop and grid cell were calculated based on long-term minimum and maximum temperatures from CGMS, optimum and minimum crop growth temperatures, the average number of days for the crop to reach maturity, and crop variety distribution (see Balkovič et al., 2018, 2013).

2.3. Regionalization of crop management practices

Two regionalization methods were used to construct representative agricultural practices for the study regions: bottom-up and top-down. The representative agricultural practices were then combined with all soil grids in the respective regions.

2.3.1. Bottom-up approach

The experimental crop rotations (LTERot) and experimental crop treatments (Cntr, NP, NP + FYM, NP + resid, and FYM) from Section 2.1 were extended to all soil grids in the respective regions. In the Hradec Králové region, experimental systems from LTE Hněvčeves were used for all cropland soils in the warmer climate (roughly below 50.4° north latitude), while LTE Trutnov was used for the moderately warm and cold climates.

2.3.2. Top-down approach

Agricultural practices were derived from cropland and land-use data reported for NUTS2 regions from 1995 to 2010 by Eurostat (the statistical office of the European Union, http://ec.europa.eu/eurostat), including crop harvested areas, crop and forage yields, fertilization

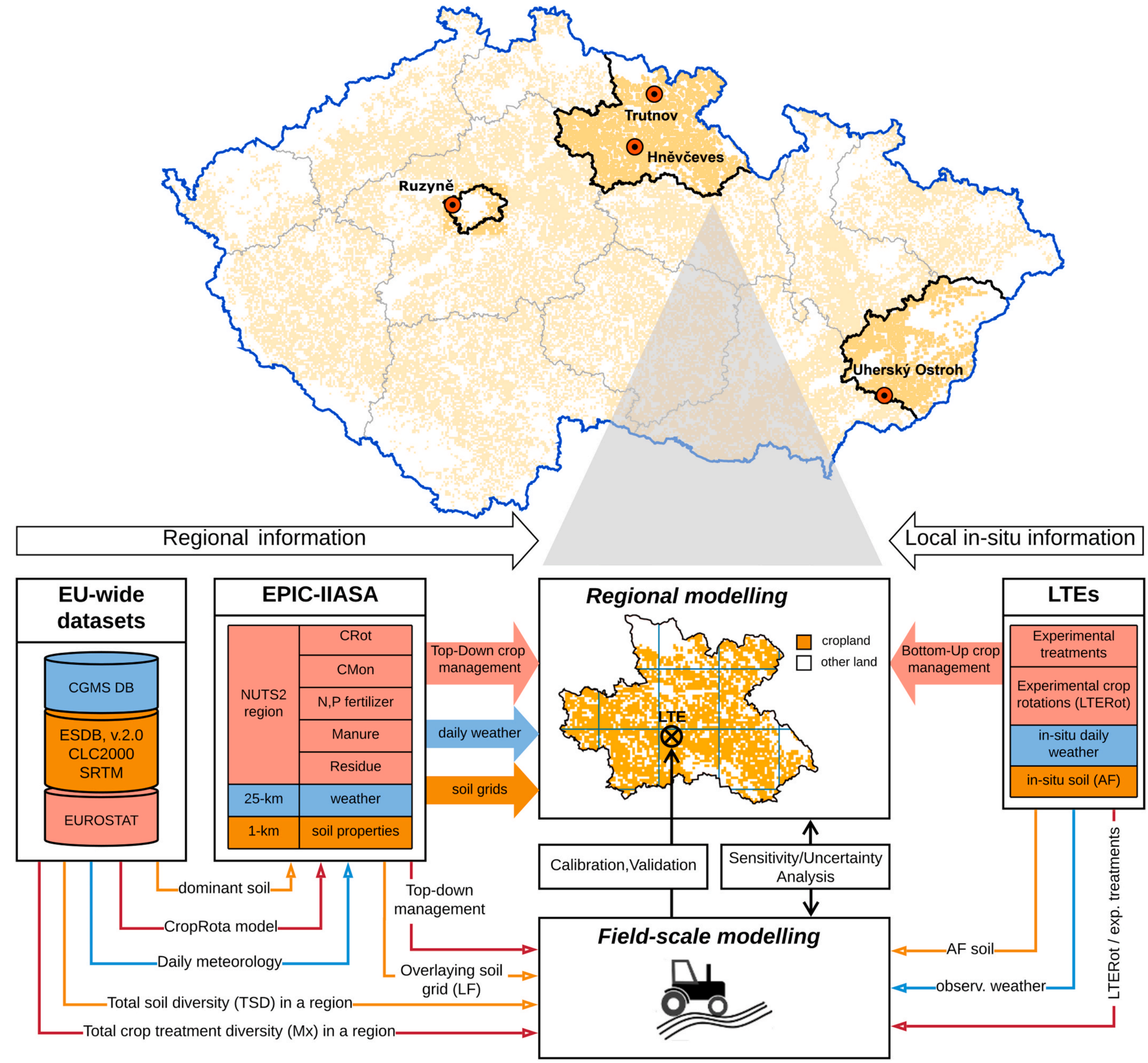

Fig. 1. Study regions with location of long-term experiments and a schematic of regional SOC modelling layout; orange colour demonstrates cropland soil information, blue colour demonstrates meteorological inputs, and red colour represents crop management inputs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

consumption, and livestock numbers. Two alternative cropping patterns were tested:

1) Crop rotations (CRot) constructed based on crop harvested areas and a matrix of main agronomic rules included in the CropRota model (Schönhart et al., 2011). Crop shares in the rotations and rotation weights (Table 2) were optimized in CropRota to reproduce crop harvested areas reported for regions in the reference period of 1995–2010.
2) Monocultures (CMon) simulating all major reported crops independently. Regional weights of individual CMon sequences were also defined based on the reported crop harvested areas aiming to meet the 1995–2010 reference period.

Crop rotation types (CRot, CMon) were combined with crop-specific nutrient inputs from EPIC-IIASA (Table 2). These inputs were estimated by computing fertilizer balances for NUTS2 regions between 1995 and 2010. The total annual nitrogen (N_{tot}) and phosphorus (P_{tot}) application rates were calculated for each crop from regional livestock numbers and excretion coefficients as well as commercial fertilizer consumption. Crop-specific fertilizer demands were calculated using regional crop and forage yields and acreages as well as nutrient uptake coefficients (Balkovič et al., 2013 and citations therein).

Consistently with the bottom-up approach, five crop treatment scenarios assuming different handling of nutrient inputs (N_{tot}, P_{tot}) and crop residues were designed:

1) NP: N_{tot} was applied as mineral N-fertilizer split in two applications: two thirds with sowing (or in early spring in case of winter crops) and one third 40 days later. Only one application was scheduled for the

Table 2
List of crop rotation (CRot) and monoculture (CMon) systems, their regional weights, crop-specific nutrient inputs, and the total cropland areas included for the study regions in EPIC-IIASA. See Table 1 for crop name abbreviations.

Region	Crop rotations and areal weights (*w*, fraction)				Nutrient inputs (in *kg ha^{-1} y^{-1}*)		
	CRot	*w*	CMon	*w*	Crop	N_{tot}	P_{tot}
Hradec Králové Region (CZ052) Cropland area: 189,080 ha	cs-bl-af-af-ww	0.358	af	0.335	af	93	17
	bl-rp-af-af-ww	0.255	ww	0.238	ww	108	12
	ot-af-af-ww-sg	0.095	bl	0.151	bl	78	10
	af-af-ww-po-ww-rp	0.076	rp	0.098	rp	108	15
	af-af-ww-rp-ww	0.067	cs	0.076	cs	130	18
	bl-ww-sg	0.057	ot	0.039	ot	62	8
	ot-ww-rp-ww	0.046	sg	0.038	sg	103	10
	ot-wr-rp	0.025	po	0.013	po	75	8
	cs-bl-mz-bl	0.016	wr	0.008	wr	80	10
	bl-ww-rp-ww	0.005	mz	0.004	mz	100	14
Zlín Region (CZ072) Cropland area: 120,260 ha	bl-rp-ww-cs	0.216	ww	0.295	ww	102	11
	bl-af-af-ww-sg	0.195	bl	0.214	bl	74	9
	bl-rp-ww-cs-ww	0.153	af	0.143	af	88	16
	po-ww-af-af-ww	0.115	rp	0.102	rp	102	14
	ot-mz-bl-rp-ww	0.089	cs	0.094	cs	120	17
	bl-ww	0.072	sg	0.052	sg	97	9
	sg-bl-po-ww	0.053	po	0.036	po	70	7
	ot-ww-ww	0.042	ot	0.032	ot	59	7
	bl-af-af-wr	0.038	mz	0.022	mz	92	7
	cs-bl	0.018	wr	0.01	wr	77	10
	mz-bl	0.009					
Capital Prague (CZ010) Cropland area: 14,220 ha	bl-rp-ww-bl-af-ww	0.253	ww	0.425	ww	110	24
	bl-ww-rp-ww	0.218	bl	0.22	bl	80	21
	po-ww-rp-ww	0.138	rp	0.131	rp	110	31
	sg-ww-ww-bl-af-ww	0.086	af	0.072	af	95	37
	ot-ww-bl	0.083	ot	0.056	ot	64	16
	cs-ww-sg-ww	0.074	sg	0.042	sg	105	21
	bl-ot-ww	0.062	po	0.035	po	76	16
	bl-af-ww	0.047	cs	0.019	cs	128	38
	ot-ww-sg-ww	0.031					
	sg-ww-bl-ww-bl	0.008					

rates of less than 50 kg N ha^{-1}. P_{tot} was applied as a single rigid amount of mineral P-fertilizer together with tillage in autumn.

2) NP + FYM: in CRot, 40 Mg ha^{-1} of farmyard manure (0.1% of mineral N, 0.5% of organic N, 0.14% of organic P, 8.5% of C) was applied once during the rotation period shortly before tillage, preferably to maize, potatoes and sugar beet, as defined in the good agricultural practice guidelines in the Czech Republic. In CMon, the same amount of farmyard manure was applied to the root crops and maize every third year. The remaining N_{tot} and P_{tot} were applied as industrial fertilizers similarly to the NP scenario.
3) FYM: 40 Mg of FYM was applied every third year in each cropping system, preferably to maize, potatoes, and sugar beet in CRot. Farmyard manure was applied shortly before tillage.
4) NP + resid: as in the NP scenario with residues of wheat, rye and barley retained.
5) Cntr: zero nutrient inputs and all crop residues harvested.

In all crop treatments we assume a conventional tillage consisting of two soil cultivation operations and a 25-cm deep mouldboard ploughing in autumn, and an offset disking shortly after harvesting of cereals. In addition, two row cultivations were simulated for maize and a ridging for potatoes. Alfalfa or oats were used instead of clover, cereal/clover mixes and other green forage except for green maize in this study. All crops were considered rainfed and soil erosion was not accounted for in our EPIC simulations since soil erosion is well controlled in the experiments.

2.4. Simulation and evaluation layout

A tier layout was designed to bridge LTEs with gridded modelling and to allow model calibration and verification, as well as studying the sources of uncertainties in SOC stock modelling from field to regional scale. The full simulation layout is presented in Table A2.

1) Plot-scale tier (T1): field-based simulations carried out using in-situ input data collected from the LTEs, including experimental soils (AF), experimental rotations (LTERot), experimental input treatments from Section 2.1, and observational weather.
2) Bottom-up regional tier (T2): gridded simulations combining all cropland soil grids in a region with CGMS weather and with experimental farming practices from the LTEs occurring in the region.
3) Top-down regional tier (T3): gridded simulations on all soil grids as in T2 with the top-down crop management setups (Section 2.3.2).

By evaluation of 1) AF soils against single soil grids overlaying directly the LTE locations (LF soil grid), 2) all soil grids in the region, and 3) the total soil input diversity in the region (see Section 2.5) we quantified the bias, variability, and uncertainty in SOC stock change values, respectively, occurring due to localization of soil inputs alone (tier 2), and in a combination with top-down crop management inputs (tier 3). A contribution of crop management regionalization alone was evaluated by including singled-out AF and LF soil inputs in tier 3. The gridded CGMS weather data were used for regional scale modelling (Section 3.3.1 and 3.3.2), while observed local weather was used for sensitivity and uncertainty analyses, model calibration and verification at locations of LTEs.

The dry-matter crop yield (YLD, in Mg ha^{-1}), the 0–25 cm SOC stock on the last day of the year (OCPD, in Mg ha^{-1}) and the mean annual SOC stock change (ΔOCPD, in Mg ha^{-1} y^{-1}) were analysed in this study. In T1 and 2, the long-term mean annual SOC stock change was calculated from LTERot as an average interannual change for each location *l* and input treatment *r* using Eq. (1).

$$\Delta OCPD_{l,r} = \frac{1}{N-1}\sum_{t=1}^{N-1} OCPD_{l,r,t+1} - OCPD_{l,r,t} \tag{1}$$

where *t* is time interval (year), and *N* is number of years over a simulation time period.

In T3, the annual SOC stock change was calculated for each *l* and *r* as an average of *M* cropping systems weighted by their regional importance (*w*) as presented by Eq. (2). Also the absolute OCPD values were weighted across individual rotations similarly as in Eq. (2).

$$\Delta OCPD_{l,r} = \sum_{c=1}^{M} w_c \cdot \Delta OCPD_{l,r,c} \tag{2}$$

where c stands for c-th crop rotation, and M is number of crop rotations in CRot or CMon scenario. Total annual OCPD gain in a region (in Gg C y^{-1}) was calculated as Eq. (3)

$$\Delta OCPD_{r} = \sum_{l=1}^{A} Area_{l,r} \cdot \Delta OCPD_{l,r} \tag{3}$$

where $Area_{l,r}$ is the cropland area in grid l in ha, and A is the total cropland area in region (Table 2). We also calculated soil C gains for a shift from control to another crop treatment as a difference between the respective $\Delta OCPD_l$ values.

2.5. Sensitivity analysis

The Sobol's total order sensitivity index (ST,Sobol, 1990) was calculated in the SimLab software (Tarantola and Becker, 2015) to rank model features according to their influence on ΔOCPD variance in tier 1 to 3. The features, their regional ranges, sampling distribution functions (SDF) and mode values, were constructed for each region from the underlaying data in the EPIC-IIASA GAM (for a sample region see Table A1). The soil input ranges and SDFs in T2 and 3 represent the total diversity of cropland soil inputs (TSD) occurring in a region, involving all soil types from the background soil maps. Most of the soil inputs were sampled by a triangular SDF, with the mode at a regionally dominant value, and the limits at regional extremes. Similarly, the SDFs of crop management inputs determine the entire crop treatment gradient (Mx) in a region, starting from zero-input and ending with high-input practices, including mineral fertilization, manuring and crop residue incorporation. A detailed description of all features in Table A1 can be found in Gerik et al. (2013).

The sensitivity analysis (SA) was performed in three cumulative steps for each LTE: by varying only EPIC biophysical parameters in the first place (step 1), soil inputs added as second (step 2), and crop management activities added as third (step 3). The observational weather data were used here. A sensitivity to biophysical parameters only was analysed in step 1 by including T1 input data and a total of 49 parameters influencing C dynamics and crop growth processes (see list in Table A1). The analysis was extended for 12 soil inputs in step 2, aiming to include also the sensitivity stemming from localization of soil inputs in T2. Finally, the analysis was extended for seven crop management inputs in step 3, aiming to analyse the influence of crop management regionalization in T3 by varying crops in a rotation system, fertilization inputs, organic amendments, residue harvesting, and tillage practices.

2.6. Uncertainty analysis

In each LTE, a total of 100,000 random combinations of biophysical parameters alone (step 1 as in Section 2.5), parameters and soil inputs (step 2), and the previous two together with crop management variables (step 3) were sampled to bracket the uncertainty in SOC stock values stemming from uncertain model parameters (T1), plus the TSD soil inputs (T2), and plus the Mx crop management (T3). Only the 20 most influential parameters from the SA in Section 2.5 step 1 were considered for this. To set the boundary conditions for a reasonable water balance, only Hargreaves parameter values resulting in a potential evapotranspiration (PET) close to values reported for the regions were used. Apart from that, all the same soil and crop management variables as in Section 2.5 were considered (see Table A1). The uncertainty analysis (UA) was carried out using on-site observed weather data to avoid uncertainties due to weather scaling. Besides the total uncertainty covering step 1 to 3, we also analysed the uncertainty of each component individually as in Section 2.5.

2.7. Model calibration

The twenty most sensitive EPIC parameters have been subjected to calibration by fitting simulated and measured OCPD and crop yields in the Cntr treatments, aiming to minimize an estimation error in each LTE. The Cntr treatments were used since crop nutrition is to a maximum possible extent dependant on organic matter dynamics when no nutrient inputs are assumed. The UA step 1 simulations were used as a calibration dataset, while the mean Root Mean Square Error (RMSE, Eq. (4), Willmott, 1982) was applied as a calibration criterion:

$$RMSE = \frac{1}{2}\left(\sqrt{\frac{\sum_{t=1}^{T}\left(OCPD_{e,t} - OCPD_{m,t}\right)^2}{T}} + \sqrt{\frac{\sum_{t=1}^{T}\left(YLD_{e,t} - YLD_{m,t}\right)^2}{T}}\right) \tag{4}$$

where the subscripts e and m stand for the estimated and the measured values, respectively, t is year, and T is the total number of years with measured data. The min-max normalization was used to bring all OCPD and YLD values into the range 0–1.

Parameters optimized at the LTE locations were further used for respective regional simulations. In the Hradec Králové region, the Hněvčeves experiment was considered representative for the warm climate area, whereas Trutnov-based calibration was used for moderately warm and cold climate areas (roughly above 50.4° north latitude). Pearson's correlation coefficient (r) and RMSE were used to evaluate the fit between calibrated EPIC outputs and measurements.

2.8. Model verification

The OCPD time series simulated at locations of LTEs in tier 1 to 3 were compared against the measured OCPD values in all corresponding crop treatments except for Cntr, for which the model was calibrated. Besides soil carbon, crop yields simulations were also verified against the observations in tier 1 and 2. In addition, the Intergovernmental Panel on Climate Change (IPCC) tier 1 land management and input factors were used to calculated a reference SOC stock change as suggested for national greenhouse gas inventories (Eggleston et al., 2006). The goodness of fit was estimated by using the RMSE value and the Pearson's r coefficient. A paired t-test and the critical values of Pearson's correlation coefficient for two-tail tests were used for hypothesis testing where appropriate. All statistical analyses and plotting in this study were done in R (R Core Team, 2016).

3. Results

3.1. Scale-dependent model sensitivity

At field scale (T1), the variance in ΔOCPD was dominated by carbon turnover rates, foremost by the microbial decay rate (P20) representing 35% (Cntr) to 60% (NP + resid) of the total variance. The effect of tillage on residue decay rate (P52) and the slow humus transformation rate (P47) ranked next with 15–35% and 5–10%, respectively, depending on crop treatments (Fig. 2). Some variation occurred across the LTE sites though (not shown). Obviously, parameters influencing crop growth became quite prominent in the Cntr treatments and under specific environments, for example the lower limit for soil nitrate concentration (P27) in Trutnov, or soil moisture parameters in the drier climate of Hněvčeves (e.g. P11, P61 in Fig. A1).

In the bottom-up regional modelling (T2), the ΔOCPD variability was more sensitive to varying soil inputs than to model parameters in all experimental crop management types (Fig. 2). In summary, TSD explained between 55% and 75% of the total ΔOCPD variance, while the initial SOC concentration (WOC) and the fraction of C in the passive pool (FHP) ranked at the top. The two soil inputs contributed 40%–70% when aggregated across all experimental practices. Also soil texture ranked

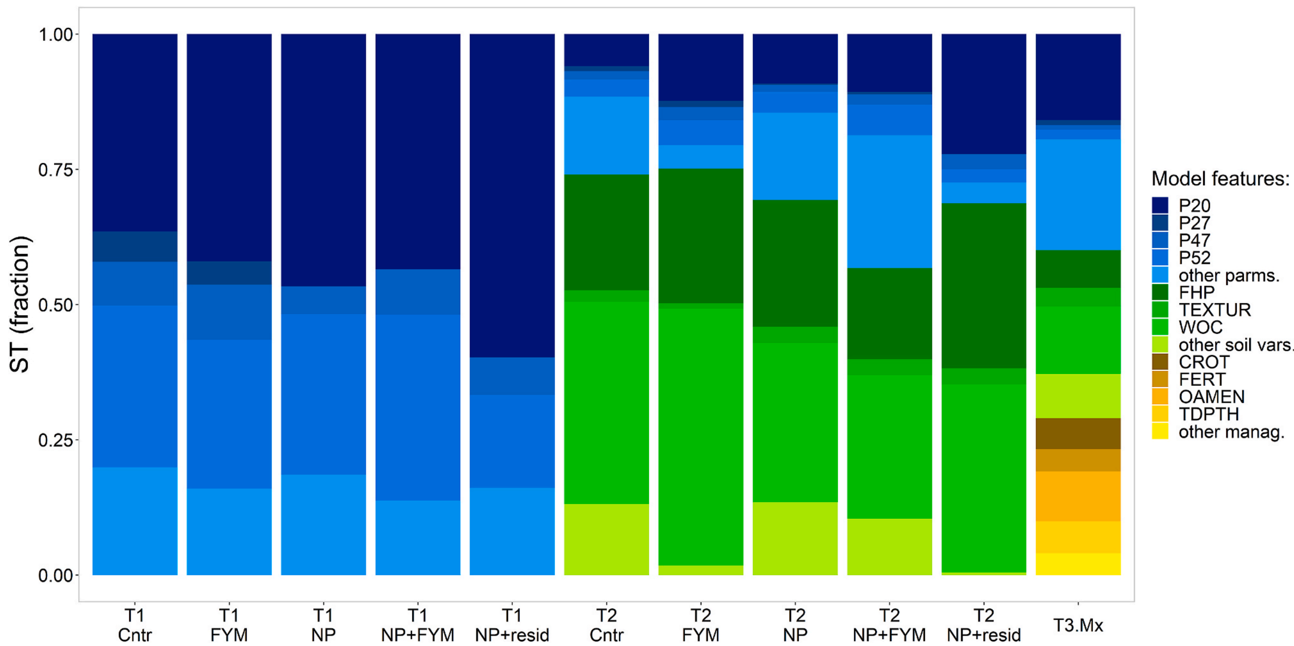

Fig. 2. Sobol's total order sensitivity index (ST) aggregated by three pools of modelling features, namely biophysical process parameters (blue), soil properties (green), and agricultural practices (yellow to brown) calculated for the mean annual SOC stock change (ΔOCPD, in Mg ha^{-1} year^{-1}). All abbreviations are listed in Table A1. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

relatively high as it constrained crop growth and root residue inputs in some soils. Mineral fertilization combined with manure amendments (NP + FYM) offset the contribution of soil inputs and biophysical parameters to a certain extent.

In the top-down regional modelling (T3), varying of regional agricultural practices within the Mx ranges controlled ~30% of the total ΔOCPD variance, with organic amendments contributing the most. In addition to crop management, P20, FHP and WOC ranked high again. In summary, EPIC-IIASA GAM was quite evenly sensitive to its parameterization, soil inputs and crop management practices, indicating a more complex feature interaction in tier 3.

3.2. Model calibration at locations of LTEs

The top 50 runs per LTE with the lowest RMSE (violin bars in Fig. 3) indicate that the most influential SOC parameters, such as P20, P52, and

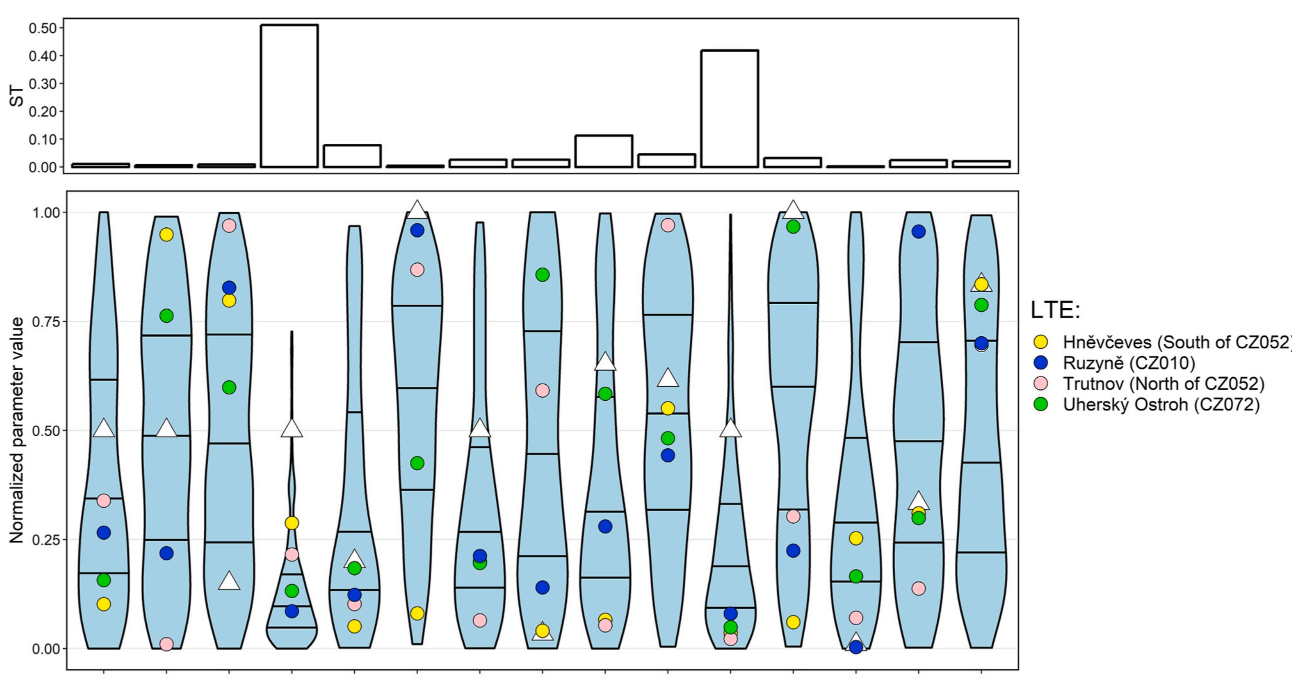

Fig. 3. The top 50 runs with the lowest RMSE collected from all long-term experiments (violins, including 25/75th percentiles and median, the normalized parameter values were used) and the most optimal parameter values calibrated at the locations of long-term experiments (coloured circles) plotted for the 15 most influential parameters; triangle: EPIC default parameter values, columns in the upper panel: the Sobol's total order sensitivity index (ST) calculated in tier 1. All abbreviations are listed in Table A1.

P47, required values from the lower tail of their respective ranges in order to meet the experimental SOC trends. A robust shift of the three parameters' values towards the lower tails indicates that robustly similar soil C parameter values are suitable for all environmental conditions in this study. In addition, parameters influencing water balance and interactions between soil moisture and crop productivity required calibration in order to minimize RMSE (e.g. P11,12, 35, 38, 61, 75, and S2 in Fig. 3). The regrowth rate of perennial crops after harvest (P69) was locally important to meet the measured alfalfa yields.

The calibration performance is presented in Fig. 4. A statistically significant correlation was established between time series of measured and calibrated OCPD and crop yield data in Trutnov, Uherský Ostroh, and Ruzyně. The SOC stock RMSE was between 1.5 and 3 Mg C ha^{-1} in the three LTEs, which is less than 6% of the background C stock. While crop yields were in a good agreement also in Hněvčeves, the OCPD time series were not significantly correlated there, and the RMSE value reached 7 Mg C ha^{-1} (~15% of the initial OCPD). It should be noted though that the experimental SOC data from Hněvčeves are very noisy and cannot be successfully fitted by any of the tested parameter combinations.

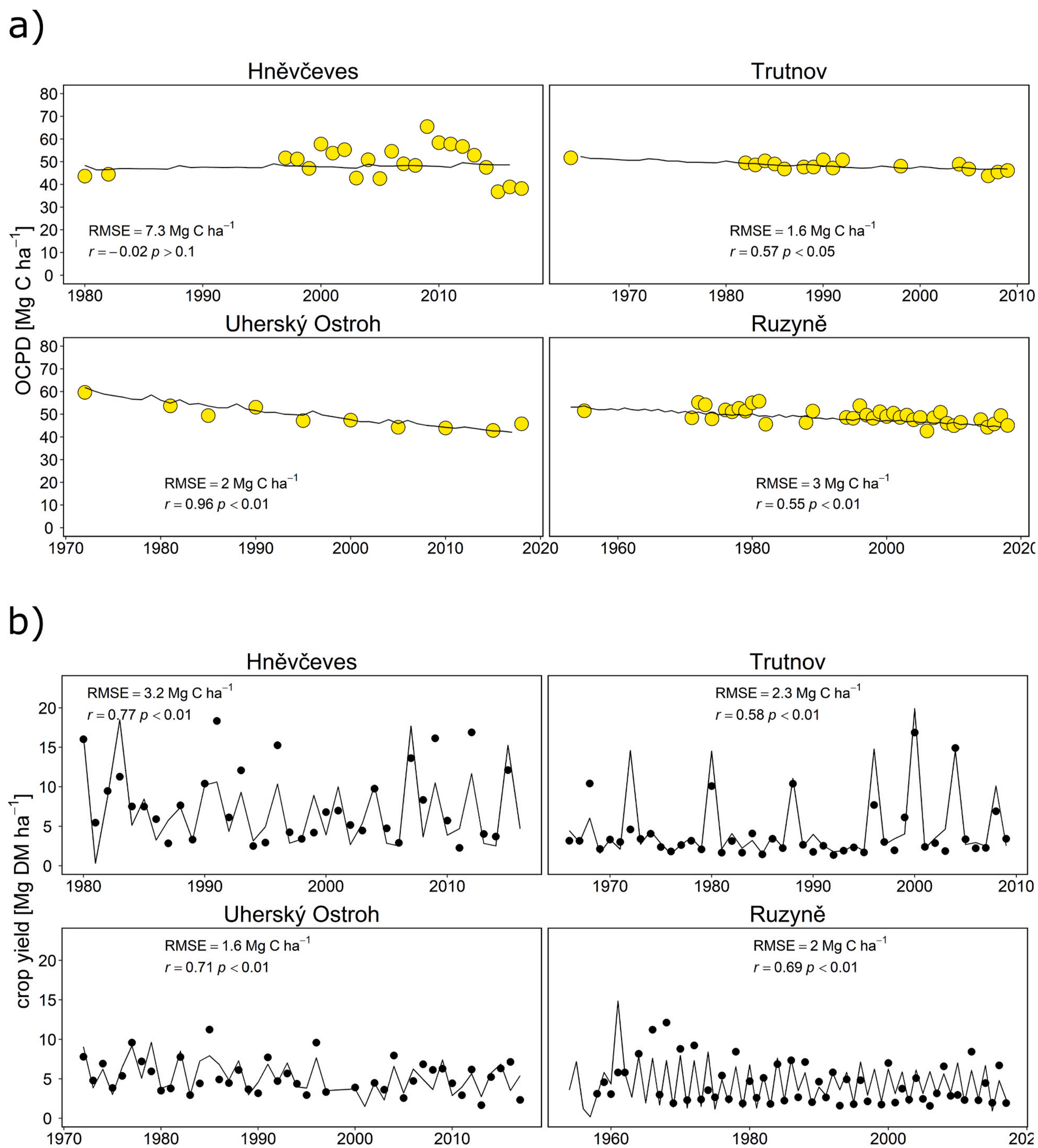

Fig. 4. Time series of simulated (lines) and measured (dots) values for a) SOC stock in 0–25 cm soil depth (OCPD, in Mg ha^{-1}), and b) dry-matter crop yield (in Mg ha^{-1}) plotted for the zero-input control treatments.

3.3. Model evaluation and verification

3.3.1. SOC stock change in the study regions

The SOC stock changes obtained from all crop management combinations and all soil grids are presented in Table 3 and Fig. A2. On average, a decrease between 0.1 and 0.3 Mg C ha^{-1} y^{-1} was estimated in the control treatment, while the impacts in soil grids ranged between slightly positive (+0.2 Mg C ha^{-1} y^{-1}) to largely negative (−0.7 Mg C ha^{-1} y^{-1}). There were substantial differences between regions and crop management setups (see total regional SOC losses shown in Fig. 5).

All studied agricultural practices enhanced soil carbon stock compared to the control scenario (Fig. 5, arrows indicate gradual changes in management from the control). Mineral fertilization contributed, on average, 0.05–0.25 Mg ha^{-1} y^{-1} more carbon than the control, which led to almost balanced SOC trends in Prague and Hradec Králové regions (under CRot and LTERot), or even a substantial sequestration ~24 Gg C y^{-1} under CMon in the Hradec Králové region. In the Zlín region, the benefits form NP fertilization were not large enough to offset the C decline and still a substantial loss of 8–13 Gg C y^{-1} was estimated in CRot and CMon. Only the LTERot method resulted in a modest sequestration of 9 Gg C y^{-1}. A shift from mineral to NP + FYM fertilization enhanced soil carbon by, on average, an additional 0.1–0.30 Mg ha^{-1} y^{-1} with substantial differences among crop management tiers: net sequestration ranged between 10 and 54 Gg C y^{-1} in the Hradec Králové region, between 9 and 27 Gg C y^{-1} in the Zlín region, and between 2 and 5 Gg C y^{-1} in the Prague region. Crop residue retention in the NP scenario provided roughly similar gains of soil C as farmyard manure amendments (NP + FYM): 0.12 to 0.23 t ha^{-1} y^{-1}. Farmyard manure alone contributed only slightly more C than NP in all tiers and regions apart from LTERot in Zlín.

It should be noted that quite contrasting SOC changes occurred among crop management tiers in the study regions. While in Hradec Králové the SOC losses were more tangible in the bottom-up approach, in the Prague and Zlín regions a higher loss occurred with the top-down crop managements, CMon more than CRot (Table 3).

3.3.2. SOC stock change in benchmark soil grids

Looking at experimental rotations with zero inputs in tier 2 first, the SOC stock changes estimated in LTEs by using experimental soils (AF) were quite distant from most soil grids in regions. More than 90% and 70% of soil grids in Prague and Hradec Králové, respectively, demonstrated faster SOC removal rates than the AF soils in this treatment (Fig. A2). On the contrary, AF soil from Uherský Ostroh were among 10% of soil grids showing the fastest C decline of all gridded soils in the Zlín region. Also the high-input treatments impacted experimental soils differently for most soil grids. In general, the gridded soils demonstrated a larger annual OCPD increase compared to Cntr than in experimental soils for all high-input management setups in Prague, and for all setups apart from CRot and CMon with FYM in the Zlín region (Fig. 5b and c). A less prominent impact of high-input management was simulated for soil grids in the Hradec Králové region though, especially in tier 2 (Fig. 5a).

Simulated SOC changes in AF soils also significantly differed from the single soil grids overlaying geographic locations of LTEs (LFs): the paired *t*-test $P < 0.01$ when all crop treatments and tiers were considered in each LTE, underlining a bias due to misallocation of soil properties to individual grids in our model. In the bottom-up tier 2, the mean bias calculated from all crop treatments was 0.04, 0.09, 0.31, and 0.48 Mg C ha^{-1} y^{-1} in Hněvčeves, Ruzyně, Trutnov and Uherský Ostroh, respectively. A similar bias occurred in the top-down tier 3: 0.03–0.17 Mg C ha^{-1} y^{-1} in Hněvčeves, ~0.12 Mg C ha^{-1} y^{-1} in Ruzyně, 0.11–0.19 Mg C ha^{-1} y^{-1} in Trutnov and 0.37–0.40 Mg C ha^{-1} y^{-1} in Uherský Ostroh, suggesting that the inappropriate allocation of soil properties affected all regionalization methods similarly.

3.3.3. Evaluation of regionally modelled SOC at locations of LTEs

The OCPD values calculated for geographical locations of LTEs were compared against SOC stock time series measured in the high-input treatments (Fig. 6). Herein, we analyse simulations obtained from the

Table 3
Regional mean initial SOC stock (OCPD, in Mg ha^{-1}) and mean annual change (ΔOCPD, in Mg ha^{-1} y^{-1}), including 1st and 99th percentiles, and the SOC stock and change values simulated in the benchmark experimental soils (AF) and soil grids overlaying long-term experiments (LF).

Region	Tier Rotation	Soils	Initial OCPD	ΔOCPD (in Mg C ha^{-1} y^{-1})				
			(in Mg C ha^{-1})	Cntr	NP	NP + resid	FYM	NP + FYM
Hradec Králové Region (CZ052)	T2LTERot	soil grids (mean)	105	−0.16	−0.11	0.01	−0.07	−0.01
		soil grids (q1,q99)	(39,212)	(−0.51,0.18)	(−0.46,0.28)	(−0.35,0.42)	(−0.39,0.26)	(−0.37,0.31)
		Trutnov AF (LF)	52 (132)	−0.05 (−0.29)	0.10 (−0.22)	0.20 (−0.10)	0.12 (−0.17)	0.23 (−0.10)
		Hněvčeves AF (LF)	46 (49)	0.01 (0.10)	0.16 (0.17)	0.27 (0.31)	0.19 (0.16)	0.30 (0.21)
	T3CMon	soil grids (mean)	105	−0.09	0.07	0.30	0.12	0.22
		soil grids (q1,q99)	(39,212)	(−0.42,0.20)	(−0.27,0.38)	(−0.03,0.69)	(−0.2,0.47)	(−0.11,0.55)
		Trutnov AF (LF)	52 (132)	−0.09 (−0.17)	0.07 (0.01)	0.29 (0.23)	0.23 (0.02)	0.24 (0.15)
		Hněvčeves AF (LF)	46 (49)	0.01 (0.11)	0.10 (0.26)	0.22 (0.48)	0.27 (0.37)	0.25 (0.42)
	T3CRot	soil grids (mean)	105	−0.15	−0.06	0.11	0.02	0.11
		soil grids (q1,q99)	(39,212)	(−0.50,0.15)	(−0.44,0.22)	(−0.27,0.38)	(−0.31,0.35)	(−0.26,0.39)
		Trutnov AF (LF)	52 (132)	−0.09 (−0.25)	0.02 (−0.14)	0.19 (0.04)	0.15 (−0.09)	0.24 (0.03)
		Hněvčeves AF (LF)	46 (49)	0.04 (0.08)	0.12 (0.13)	0.25 (0.28)	0.21 (0.27)	0.28 (0.30)
Zlín Region (CZ072)	T2LTERot	soil grids (mean)	98	−0.23	−0.01	0.15	−0.13	0.14
		soil grids (q1,q99)	(38,197)	(−0.58,0.01)	(−0.36,0.22)	(−0.18,0.37)	(−0.44,0.1)	(−0.19,0.38)
		Uherský Ostroh AF (LF)	58 (60)	−0.44 (−0.09)	−0.39 (0.13)	−0.25 (0.29)	−0.29 (0.0)	−0.27 (0.28)
	T3CMon	soil grids (mean)	98	−0.31	−0.19	−0.03	−0.12	0.0
		soil grids (q1,q99)	(38,197)	(−0.68, −0.07)	(−0.57,0.06)	(−0.38,0.20)	(−0.45,0.11)	(−0.33,0.24)
		Uherský Ostroh AF (LF)	58 (60)	−0.45 (−0.17)	−0.40 (−0.05)	−0.28 (0.09)	−0.27 (0.0)	−0.26 (0.12)
	T3CRot	soil grids (mean)	98	−0.31	−0.14	0.02	−0.08	0.13
		soil grids (q1,q99)	(38,197)	(−0.68, −0.06)	(−0.52,0.09)	(−0.31,0.23)	(−0.40,0.15)	(−0.20,0.37)
		Uherský Ostroh AF (LF)	58 (60)	−0.45 (−0.16)	−0.41 (−0.01)	−0.29 (0.14)	−0.24 (0.04)	−0.23 (0.25)
Capital Prague Region (CZ010)	T2LTERot	soil grids (mean)	48	−0.23	0.03	0.23	0.09	0.29
		soil grids (q1,q99)	(39,59)	(−0.40, −0.09)	(−0.15,0.20)	(0.09,0.37)	(−0.07,0.23)	(0.11,0.47)
		Ruzyně AF (LF)	53 (40)	−0.07 (−0.10)	0.10 (0.18)	0.28 (0.36)	0.17 (0.22)	0.29 (0.45)
	T3CMon	soil grids (mean)	48	−0.31	−0.14	0.04	0.04	0.09
		soil grids (q1,q99)	(39,59)	(−0.49, −0.14)	(−0.34,0.04)	(−0.15.0.20)	(−0.14,0.20)	(−0.11,0.27)
		Ruzyně AF (LF)	53 (40)	−0.17 (−0.16)	−0.06 (0.02)	0.07 (0.19)	0.07 (0.19)	0.11 (0.25)
	T3CRot	soil grids (mean)	48	−0.29	−0.11	0.06	0.10	0.20
		soil grids (q1,q99)	(39,59)	(−0.48, −0.12)	(−0.31,0.06)	(−0.11,0.21)	(−0.08,0.26)	(0,0.38)
		Ruzyně AF (LF)	53 (40)	−0.16 (−0.14)	−0.05 (0.05)	0.08 (0.20)	0.13 (0.24)	0.18 (0.37)

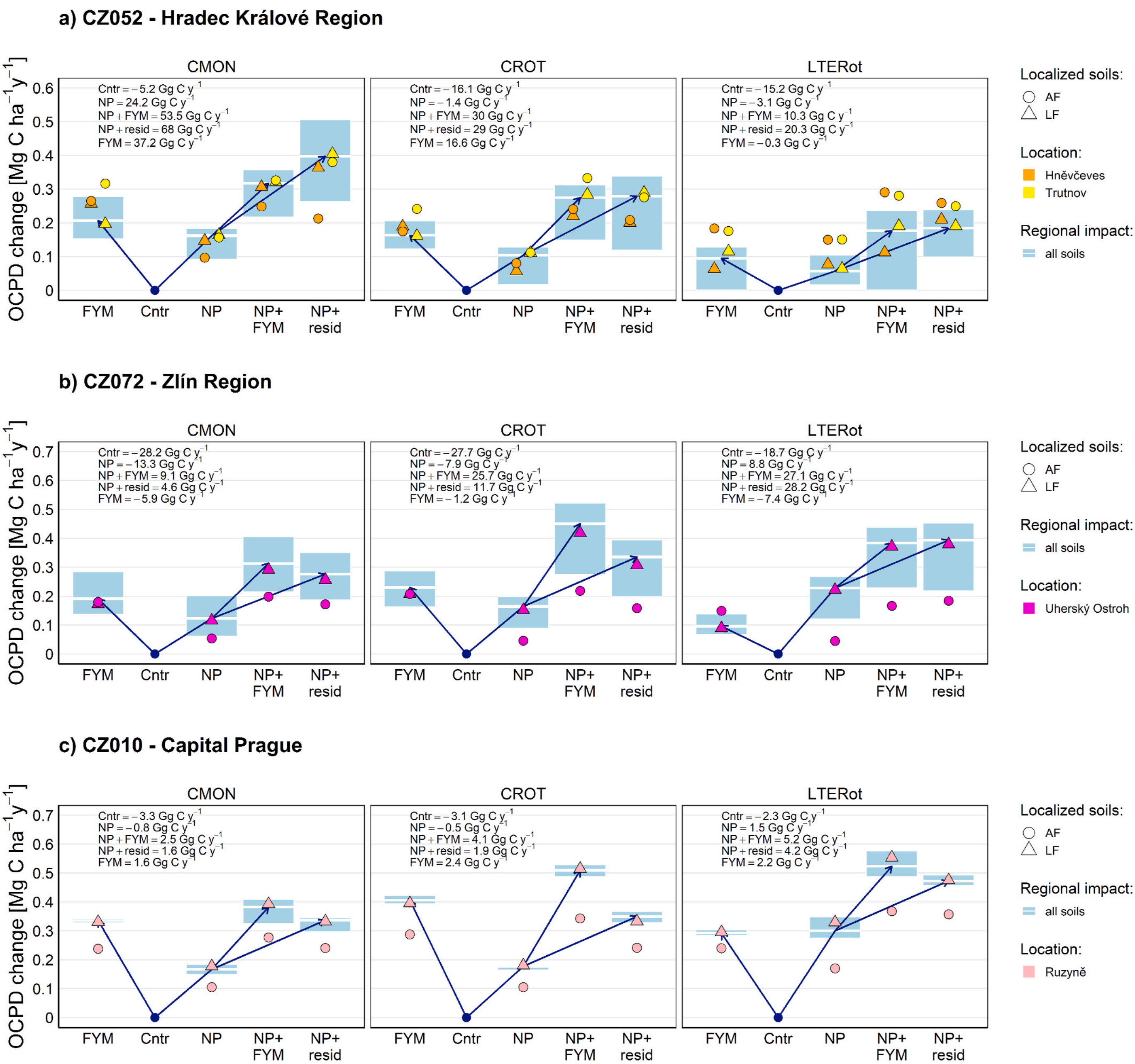

Fig. 5. The relative impact of agricultural practices expressed as a mean annual OCPD change (in Mg ha^{-1} y^{-1}) estimated in the respective crop treatments relative to the zero-input control treatment (Cntr). Annotations represent the total annual SOC stock changes (in Gg C) aggregated for the entire cropland in the regions. Panel columns represent the top-down (CRot, CMon) and the bottom-up (LTERot) regionalization of crop management (see Tables 1 and 2). Arrows indicate gradual changes in management from the control.

benchmark AF soils only, avoiding thus the bias due to misallocated soil properties described in the previous section. An extended analysis showing LF soil grids can be found in Fig. A3.

The bottom-up approach yielded an overall RMSE of 4.8 Mg C ha^{-1}, ranging from 2.2 Mg C ha^{-1} in Uherský Ostroh (NP + FYM) to 6.8 Mg C ha^{-1} in Hněvčeves NP + FYM treatment. The RMSE values were similar or even lower than those obtained in the calibration runs with Cntr in Hněvčeves and Uherský Ostroh (Fig. 4), whereas slightly larger RMSE values were estimated in Trutnov. A satisfactory validity in crop yield modelling is demonstrated in Fig. A4.

In the top-down approach, CRot and CMon rotations provided RMSE comparable with LTERot, especially in Uherský Ostroh. The overall RMSE was 5.3 and 5.5 Mg C ha^{-1} in CRot and CMon, respectively, indicating only a small deterioration of model performance in comparison with experimental rotations. The CMon approach yielded RMSE like CRot in all verification cases except for FYM and NP + resid in Trutnov. All simulations were significantly correlated with the measurements, except for NP treatments in Hněvčeves, Ruzyně and Trutnov, where the measured SOC data demonstrated no obvious trend or were too noisy.

In general, the simulated SOC stock values provided a better fit with measurements than the IPCC-based estimates, where the overall RMSE reached up to 11.4 Mg C ha^{-1}. The largest disagreement with a strongly negative correlation occurred in Uherský Ostroh, and in all FYM-related treatments in other LTEs.

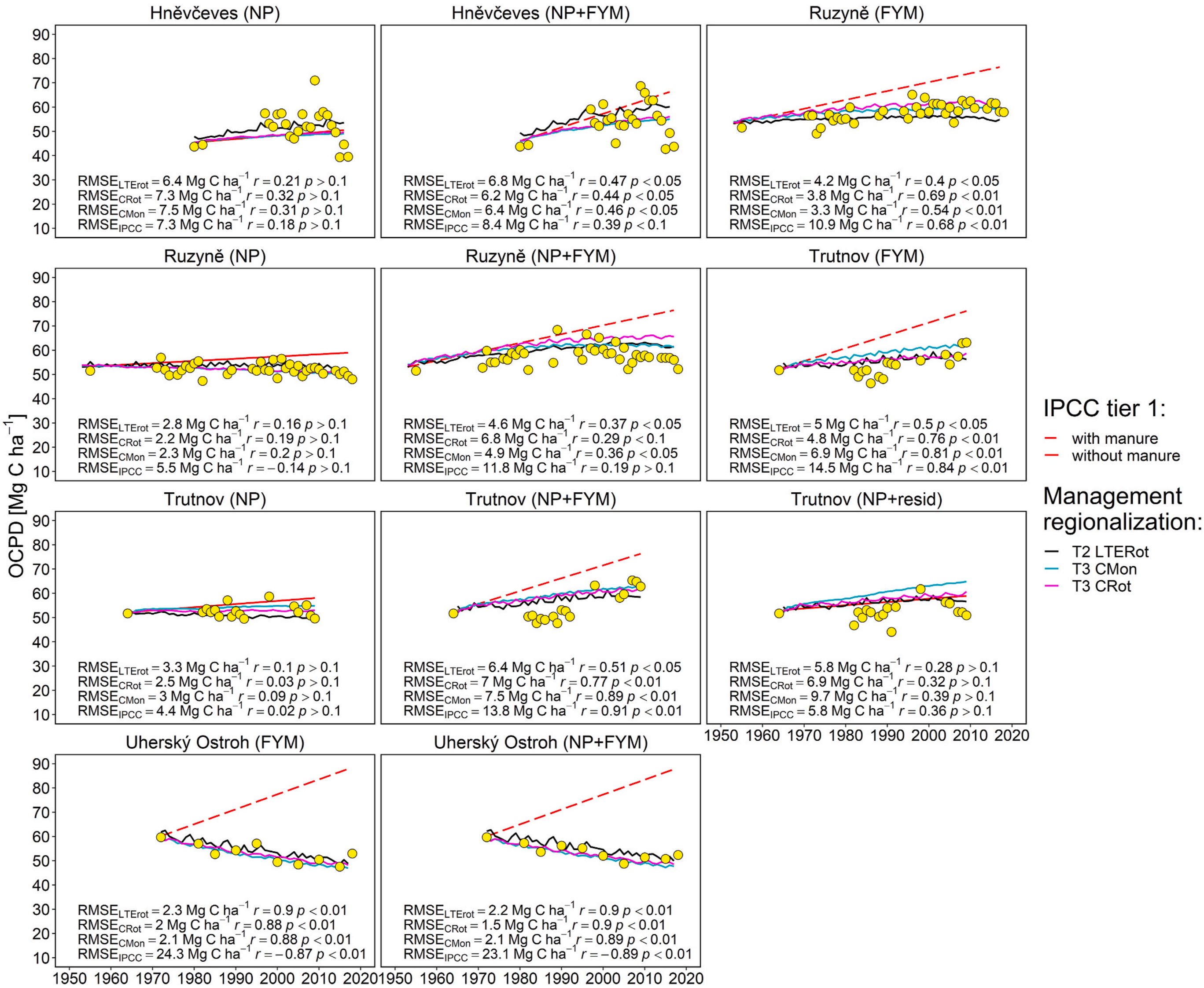

Fig. 6. Model verification calculated at locations of long term experiments with the experimental AF soils and observational weather. Measured SOC stock time-series (OCPD, in Mg C ha^{-1}) plotted against the OCPD values simulated in tier 2 and 3 with experimental (LTERot) and regionalized (CRot, Cmon) crop management as well as the estimates calculated using the IPCC tier 1 land-management and input factors.

3.4. Model uncertainty at local to regional scale

Permutation of model parameters at field scale (tier 1) resulted in the uncertainty range roughly from 0.7 (Ruzyně) to 1.8 (Uherský Ostroh) Mg C ha^{-1} y^{-1} when the 3σ intervals were considered (Fig. 7). The differences among crop treatments contributed ~0.3 Mg C ha^{-1} y^{-1} (whiskers in Fig. 7).

Extension of the tier 1 analysis for uncertain soil inputs in the bottom-up regional modelling (tier 2) almost doubled the uncertainty range in all LTEs: between 1.7 Mg C ha^{-1} y^{-1} in Trutnov and 2.9 Mg C ha^{-1} y^{-1} in Uherský Ostroh. Soil properties alone contributed 0.4–1.0 Mg C ha^{-1} y^{-1} when analysed throughout all LTEs and input treatments, which is only slightly less than the uncertainty stemming from model parametrization examined in tier 1, especially in Trutnov and Hněvčeves. The smallest soil-related uncertainty was in Ruzyně, which is a relatively small region with quite homogeneous soils.

An uncertainty range between 2.2 and 3.7 Mg C ha^{-1} y^{-1} was observed in the top-down regional modelling (tier 3). Here the uncertainty stemming from model parameters, regional soil inputs as well as crop management regionalization is accumulated. In a comparison with the bottom-up tier 2 approach, the total uncertainty increased by an additional 0.5–1.5 Mg C ha^{-1} y^{-1} in tier 3 due to the combined effect of uncertain input treatments and crop rotations in Hněvčeves, Trutnov and Uherský Ostroh. The wheat-sugar beet rotation reported for the LTE Ruzyně yielded a larger uncertainty range than all regionally generated crop rotation systems (Fig. 7c). With involvement of the calibrated EPIC model and only the experimental AF soils in tier 3, the uncertainty due to crop management alone was 0.7–1.5 Mg C ha^{-1} y^{-1}, which is comparable (Uherský Ostroh) or higher than the contribution of uncertain soils in tier 2. Finally, the uncertainty stemming from CMon is slightly larger than the uncertainty under CRot in tier 3.

The bottom-up and the top-down setups yielded significantly different ΔOCPD distributions when the entire regional gradient of crop treatments (Mx) and the entire soil input diversity (TSD) were considered (Fig. 8a). The top-down impacts were, on average, by 0.2–0.35 Mg C ha^{-1} y^{-1} lower and 1.5 to 2.5-times more variable than in the bottom-up method. Looking at AF soils alone in Fig. 8b, the Mx treatments yielded, on average, a slightly more positive SOC impact under crop monocultures than in crop rotations for all experimental sites except for the cooler climate in Trutnov. More importantly, crop monocultures yielded more variable ΔOCPD values than crop rotations (see inter-percentile ranges in Fig. 8b). For example, in the Hradec Králové

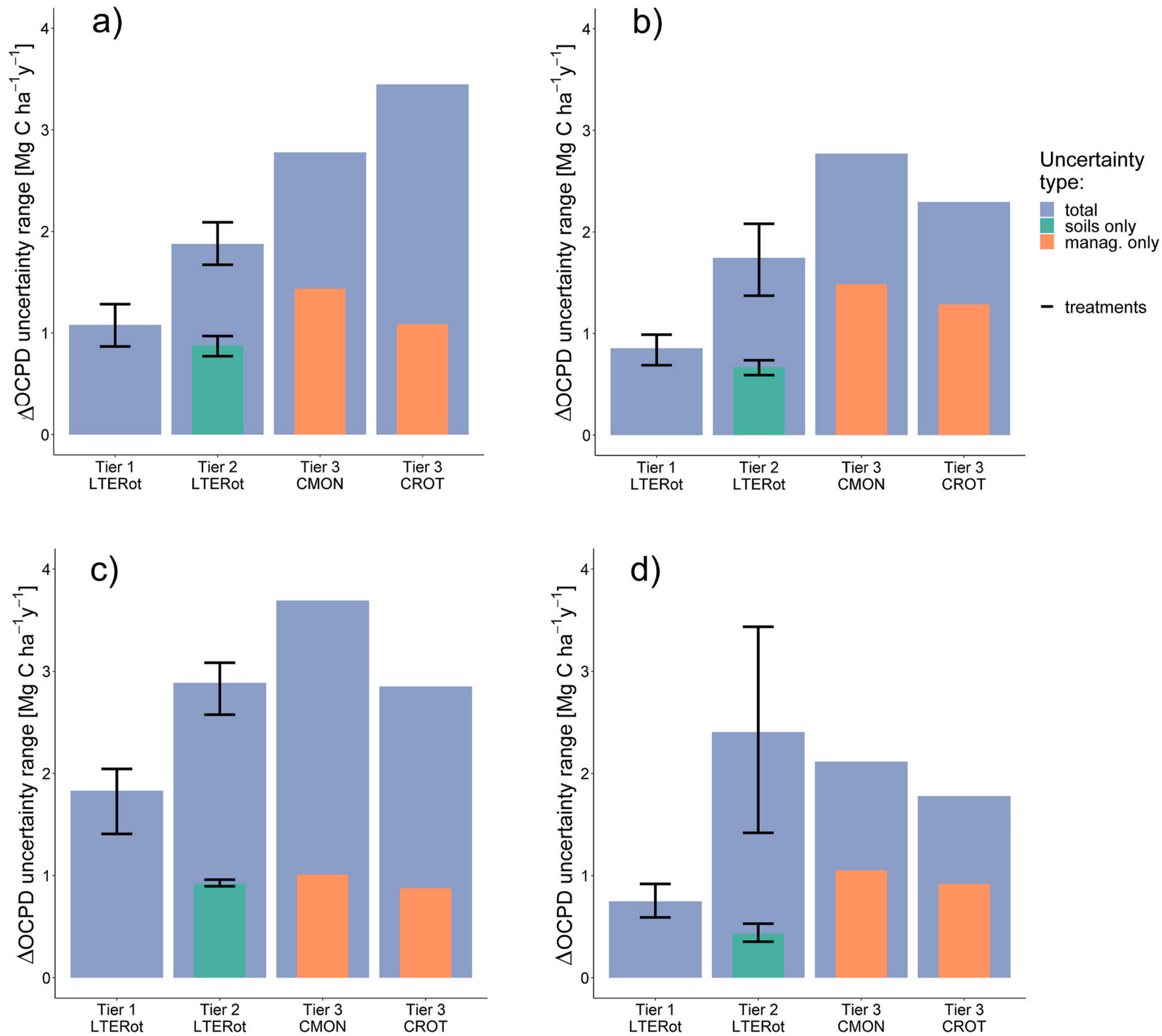

Fig. 7. Uncertainty range in the mean annual carbon change (ΔOCPD, in Mg ha^{-1} year^{-1}) in tier 1 to 3 calculated for a) Hněvčeves, b) Trutnov, c) Uherský Ostroh, and d) Ruzyně. Bars in tier 1 and 2 demonstrate an average calculated from the uncertainties of individual experimental crop treatments, while whiskers represent minimum and maximum uncertainty from the experimental treatments. Bars in tier 3 represent the total uncertainty range, including perturbed crop management. Both bars and whiskers are plotted for the 3σ confidence interval.

region, CMon realizations with high-input fertilization and crop residue treatments (upper quartile of the dashed orange distribution in Fig. 8b, left panel) resulted in a more positive impact on SOC stock than CRot for similar site conditions as in Hněvčeves. This pattern was mainly due to recurrent alfalfa and high-input cereal production in CMon (Fig. A5).

4. Discussion

4.1. Simulated SOC stock changes following agricultural practices

Following thorough EPIC model calibration, a robust increase in SOC stock following mineral NP fertilization, farmyard manure addition and crop residue incorporation compared to no-input practices has been shown in Fig. 5. Former studies suggest that the effect of mineral fertilization varies by soil texture and agro-climatic conditions, while a robustly positive impact occurs only at higher application rates as in our case (Blair et al., 2006; Sandén et al., 2018). A statistically significant increase in OCPD by 5–12% simulated for the NP treatments at the locations of LTEs (Table A3) agrees with a recent meta-analysis carried out by Sandén et al. (2018) who demonstrated only a small positive stimulus ~7% of mineral fertilization compared to no fertilization. Organic fertilization is among the main drivers of C sequestration in European soils (Bai et al., 2018; Blair et al., 2006; Powlson et al., 1998; Šimon et al., 2011). Sandén et al. (2018) demonstrated that FYM applications increased soil C stock by ~17% compared to mineral fertilization, which is in a good agreement with an increase by 8–15% and 4–8% for NP + FYM and FYM treatments, respectively, simulated at locations of LTEs in our study (Table A3). Similarly, Abbas et al. (2020) reported that manure can increase SOC by about 0.10 Mg C ha^{-1} y^{-1} when applied as organic fertilizer during a long-term experiment. In accordance with findings published by Blair et al. (2006), the application of NP-fertilisers with FYM increased SOC only marginally, by 2–6%, compared to just FYM. Additional mineral fertilizer can hence offset yield and biomass decreases compared to FYM application alone and thereby further increase residue production. Crop residue incorporation is expected to support soil C accumulation especially in the northern EU regions, in soils with higher clay content, and after a longer duration, with an overall impact of +7% compared to no residue retention (Sandén et al., 2018). In a review of SOC dynamic in managed cropland, Abbas et al. (2020) reported a 14% increase in SOC stock after incorporation of straw from intensive wheat and maize systems. In our study, the SOC stock increased by 7–12% at locations of LTE following NP-fertilization with

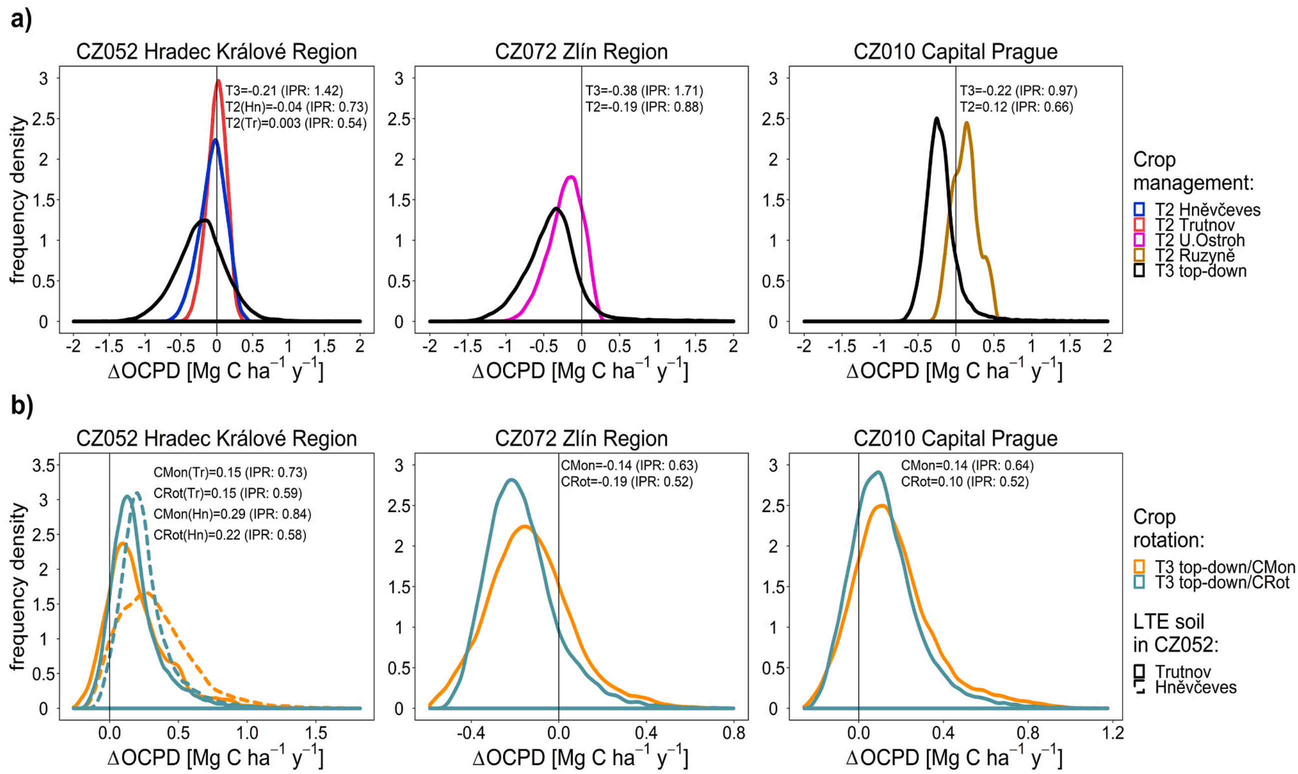

Fig. 8. Distribution of ΔOCPD simulated a) for the entire crop treatment gradient (Mx) and the total regional soil diversity (TSD) resulted from the uncertainty analysis runs with the bottom-up (T2) and the top-down (T3) regionalization approaches, and b) for the entire crop treatment gradient and experimental soils (AF) simulated with the top-down Crot and Cmon approaches; text annotations show the mean and inter-percentile range between 5th and 95th percentiles (IPR) values.

residue incorporation compared to just mineral fertilization (Table A3), which is again in a good agreement with the review studies cited above.

4.2. Localization of soil properties

Earlier studies have shown that inaccurate soil inputs may cause a significant bias in crop model outputs (Coucheney et al., 2018; Folberth et al., 2016; Grosz et al., 2017; Pogson et al., 2012). Therefore, it comes as no surprise that our model was highly sensitive to soil inputs in both bottom-up and top-down applications (Fig. 2). The total regional diversity in soil inputs (TSD) yielded an uncertainty of ~0.5–1.1 Mg C ha^{-1} y^{-1} in tier 2 (Fig. 7), which is about 1.5 to 5-times larger than the ranges in mean ΔOCPD values obtained across experimental agricultural practices in Table 3. Therefore, localization of soil properties may not only bias SOC change reported at regional scale (Coucheney et al., 2018; Grosz et al., 2017), but it may also outweigh the potential benefits expected from good agricultural practices. A similar effect of soil-related uncertainty has been demonstrated in crop yield modelling by Folberth et al. (2016). Besides, soil grids not matching field conditions may compromise the model verification at locations of carbon monitoring systems.

The initial SOC concentration and soil C in the passive pool, followed by the particle size distribution, turned out as the most influential soil inputs in our study (Fig. 2). Indeed, soil C concentration and passive C pool are closely associated with land use and land use change activities (Eggleston et al., 2006) and they are the key soil properties for biophysical carbon modelling (Basso et al., 2011; Hashimoto et al., 2011; Lugato et al., 2014). As also demonstrated by our UA results, a proper initial SOC and passive C concentration is an essential condition for quantification of land use impacts by biophysical models (e.g. Lugato et al., 2014). For example, at the Trutnov site, soils initially poor in humus sequestered C under all initial soil conditions except for those with a sandy texture, whereas soils initially richer in humus sequestered C only when medium-fine or finer, and only when dominated by the passive C pool (Fig. A6). Since the passive C pool cannot be directly related to any measurable C fraction (Izaurralde et al., 2006; Zimmermann et al., 2007), a good estimation of C pools is often dependent on a long-term spin up or an initial partition function (Basso et al., 2011). Based on literature from the region (see Section 2.1), the long-term cropland cultivation history in the study area, the large content of heavy C fraction in the experimental soils, and findings from similar LTEs (Izaurralde et al., 2006), we assumed that 75% of soil C occurred in the passive pool. It should be noted that bulk density has not been consistently monitored in long-term experiments, which weakens the comparability between experimental carbon stock and model outputs.

4.3. Regionalization of crop management

Top-down approaches are a common practice in largescale modelling (Balkovič et al., 2013; Elliott et al., 2015; Müller et al., 2016; Van der Velde et al., 2009). A concern is that cropping systems which are based on regional statistics or large-scale datasets may not represent on-ground management (Folberth et al., 2019). Therefore, a bottom-up approach combining calibrated local runs with upscaling methods has been preferred by some authors to produce locally relevant regional results (van Ittersum et al., 2013). However, a lack of detailed crop management and experimental data for large regions (Smith et al., 2020) may limit the applicability of bottom-up modelling.

In Section 3.3.1 we pointed out that significant, region-specific differences occurred among regionalization approaches due to interactions between crop management, soil grids, and heterogeneous climatic conditions represented by gridded weather. To unravel the effects of crop management from spatially heterogeneous weather, herein we discuss the runs carried out exclusively with observational weather as designed in the UA (Section 2.6). Apparently, as demonstrated in Fig. 8a for the entire range of soils, the top-down T3 method, which includes a larger variety of crop management combinations such as different crop sequences, fertilization intensities, manure applications, soil tillage and crop residue handling compared to the bottom-up approach, led to a more dispersed soil C impact distribution. In contrast, experimental crop rotations are often adapted to local conditions and include measures to reduce C losses, such as catch crops or intercropping, which may be missing in top-down regional setups. A positive impact of the complex crop rotations, such as those in Trutnov and Hněvčeves for example, is clearly underestimated in the top-down approach.

Crop monocultures have been extensively used in largescale crop modelling (Müller et al., 2016; Rosenzweig et al., 2014). A concern regarding soil C might be that recurrent monocrops do not account for a positive effect of crop rotations on SOC stock and crop yields (Bai et al., 2018; Constantin et al., 2010; Hernanz et al., 2002; Mazzoncini et al., 2011; Tatzber et al., 2009). It is worth noting though that some authors reported a neutral effect of crop rotation on soil carbon, while still highlighting a positive effect on crop yields (Sandén et al., 2018). In Section 3.3.1 we have shown a slightly more positive impact of CMon in the Hradec Králové region and CRot in Prague and Zlín. When excluding climate interference in the UA, crop rotations and monocultures yielded only a slightly different SOC impact distribution, while crop monocultures demonstrated a larger variability in the SOC change values (Fig. 8b). Given a large share of alfalfa, used herein to represent all green forage except for silage maize, and a substantial share of cereals in the study regions, a more positive effect of CMon in contrast to CRot in some parts may be caused by a positive impact of alfalfa and a high residue incorporation from recurrent high-input cereals. High sequestration potential of winter cereal-based systems due to the high amount of crop residues left in the field was also concluded by Gaiser et al. (2009), while a positive effect of alfalfa and other legumes on soil C was observed by Su (2007) and VandenBygaart et al. (2003). The differences between CRot and CMon faded away under the full soil diversity (Fig. A7) though, indicating that soil input variability may offset the effect of cropping patterns in regional aggregation. It should be emphasized that in the UA we did not explore the whole range of climatic conditions.

4.4. Other model limitations

Apart from the limitations discussed above, our platform is also subject to uncertainty related to aggregation of weather data (Angulo et al., 2013; Zhao et al., 2015). Albeit, average unbiased estimates of weather data aggregated at a regular grid are generally assumed pragmatic solutions for large-scale modelling (Rosenzweig et al., 2014).

A few studies have shown that soil erosion influences the regional carbon cycling as it is an important driver of SOC redistribution across the landscape (Berhe et al., 2007; Doetterl et al., 2016). However, a gap in coupling of erosion and distribution processes in the EPIC-IIASA model prevented us from addressing soil erosion in this study. Besides, the experimental data did not allow for an erosion-induced C dynamics calibration as soil erosion was well controlled in the long-term experimental plots. A deeper process understanding, and more detailed large-scale data, would be needed to address impacts of erosion on regional soil C budgets.

Our study highlights that model calibration and verification are important preconditions for reliable SOC modelling. While the growing number of field measurements can inform on the actual SOC stock in the landscape (Panagos et al., 2013b, 2013a), only long-term experiments or monitoring systems can support the temporal SOC dynamics assessments (Rumpel et al., 2018; Smith et al., 2020). This constrain is given by the fact that the SOC changes between agricultural treatments are detectable only after years or decades of cultivation (Campbell et al., 2000; Janzen et al., 1998). A limited number of long-term experiments and monitoring systems (Debreczeni and Körschens, 2003; Jandl et al., 2014; Lorenz et al., 2019) may therefore impose a real challenge for large-scale SOC modelling.

It should be emphasized that the mean annual rates in SOC stock change calculated from all sequential interannual changes in Eq. (1) differ from the definition proposed by IPCC for national greenhouse gas monitoring (Eggleston et al., 2006). In the IPCC methodology, the annual rates in SOC change are calculated from a linear trend as the difference in stocks in the first and last year divided by the number of years over an inventory period. Since we explore, among others, the model's sensitivity under rotated crops and agricultural practices, a measure based on interannual SOC change is more appropriate in our study. A comparison presented in Fig. A.9 suggests that our annual rates are satisfactorily comparable with the IPCC method.

5. Conclusions

Soil carbon changes simulated by the EPIC-IIASA GAM platform in the study regions of Czech Republic were almost evenly conditioned by 1) model calibration, 2) soil input localization, and 3) crop management regionalization. Each of the three components may compromise SOC change reporting and verification since the uncertainty implied by each of those is substantially larger than the actual impact of varying agricultural practices on SOC dynamics.

Provided that more than 80% of the parameter combinations in the tier 1 uncertainty analysis overestimated the SOC losses compared to the calibrated simulations (see example in Fig. A8), there is a high probability that process-based agronomic models such as EPIC might miscalculate the SOC trends under individual agricultural practices if not properly calibrated. At the same time, model calibration for a variety of climatic and soil conditions in the Czech Republic resulted in similar C parameter values, pointing to a robust scalability of the EPIC-IIASA GAM platform. Nevertheless, a large model sensitivity to biophysical parameters underlines the importance of model calibration against a network of long-term experiments or observations as a prerequisite for verifiable modelling. Cooperation platforms bringing field measurements and field experiments to a wider scientific community, such as in the CIRCASA project (https://www.circasa-project.eu), are therefore indispensable to facilitate soil carbon modelling.

A proper localization of key soil properties, including initial SOC, its partitioning into C pools and soil texture, is another precondition for reliable regional reporting and model verification at benchmark plots. Inaccurate soil inputs obtained from the background soil maps at the location of LTE may largely bias the simulated SOC trends. The uncertainty due to localization of soil map data to single grid cells is larger than the true SOC impacts estimated among agricultural practices. Our results emphasize the importance of more accurate and more accessible soil information at high spatial resolution.

Cropping practices were among the most influential drivers in our study. Importantly, the top-down management setups following regional land-use statistics proved suitable for the estimation of SOC dynamics consistently with actual practices in the field, enabling thus reasonable model verification at locations of LTEs. In general, crop rotations performed better than the commonly used monocultures. The model performed better than the generic land-management and input factors employed in the IPCC tier 1 methodology, which suggested an opposite direction of SOC dynamics in some cases. This indicates a great model's potential for improved carbon modelling over larger political regions. The case study provides a template for gridded SOC modelling across regions, accounting for the uncertainty due to regional variability in soils and the need to derive representative agricultural management inputs at regional scale.

CRediT authorship contribution statement

Juraj Balkovič: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Mikuláš Madaras:** Conceptualization, Data curation, Resources. **Rastislav Skalský:** Conceptualization, Investigation. **Christian Folberth:** Conceptualization, Writing - original draft. **Michaela Smatanová:** Resources. **Erwin Schmid:** Methodology.

Marijn van der Velde: Conceptualization, Writing - original draft. **Florian Kraxner:** Supervision, Project administration. **Michael Obersteiner:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2020.111206.

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